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Agricultural conservation practices can help mitigate the impact of climate change

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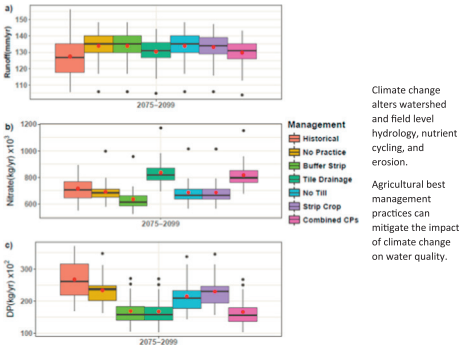
HIGHLIGHTS

- Climate change impacts hydrology, nutrient cycling and erosion potentially degrading water quality
- Agricultural conservation practices can mitigate the impact of climate change on water quality
- Targeting on critical source areas results in nearly the same water quality protection as widespread targeting

GRAPHICAL ABSTRACT

Climate change alters watershed and field level hydrology, nutrient cycling, and erosion.
Agricultural best management practices can mitigate the impact of climate change on water quality.



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ABSTRACT

Agricultural conservation practices (CPs) are commonly implemented to reduce diffuse nutrient pollution. Climate change can complicate the development, implementation, and efficiency of agricultural CPs by altering hydrology, nutrient cycling, and erosion. This research quantifies the impact of climate change on hydrology, nutrient cycling, erosion, and the effectiveness of agricultural CP in the Susquehanna River Basin in the Chesapeake Bay Watershed, USA. We develop, calibrate, and test the Soil and Water Assessment Tool-Variable Source Area (SWAT-VSA) model and select four CPs; buffer strips, strip-cropping, no-till, and tile drainage, to test their effectiveness in reducing climate change impacts on water quality. We force the model with six downscaled global climate models (GCMs) for a historic period (1990–2014) and two future scenario periods (2041–2065 and 2075–2099) and quantify the impact of climate change on hydrology, nitrate-N (NO_3-N), total N (TN), dissolved phosphorus (DP), total phosphorus (TP), and sediment export with and without CPs. We also test prioritizing CP installation on the 30% of agricultural lands that generate the most runoff (e.g., critical source areas-CSAs). Compared against the historical baseline and with no CPs, the ensemble model predictions indicate that climate change results in annual increases in flow (4.5 ± 7.3%), surface runoff (3.5 ± 6.1%), sediment export (28.5 ± 18.2%) and TN export (9.5 ± 5.1%), but decreases in NO_3-N (12 ± 12.8%), DP (14 ± 11.5), and TP (2.5 ± 7.4%) export. When agricultural CPs are simulated most do not appreciably change the water balance, however, tile drainage and strip-cropping decrease surface runoff, sediment export, and DP/TP, while buffer strips reduce N export. Installing CPs on CSAs results in nearly the same level of performance for most practices and most pollutants. These results suggest that climate change will influence the performance of agricultural CPs and that targeting agricultural CPs to CSAs can provide nearly the same level of water quality effects as more widespread adoption.

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1. Introduction

Climate change has the potential to impact hydrology and diffuse nutrient export from agricultural landscapes (Ahmadi et al., 2014; Howarth et al., 2006; Records et al., 2014). In the humid temperate Eastern US, climate predictions suggest that precipitation quantity (during the winter/spring), and intensity (during the growing season) will continue to increase, which cause greater diffuse nutrient and sediment export from agricultural landscapes (Chang et al., 2001; Cousino et al., 2015). This increased export has a number of deleterious consequences for receiving water bodies; accelerated eutrophication, and harmful algal blooms (Burgin and Hamilton, 2007), undesirable changes in the river structure and function, and decreasing storage capacity or flood control of reservoirs (Cerco, 2016; DePhilip and Moberg, 2010). In addition, the loss of valuable nutrients and topsoil from agricultural fields decreases productivity or increases management intensity (Lal, 1998).

Agricultural conservation practices (CPs) are increasingly and widely used to reduce impact of diffuse pollutant export from agricultural landscapes (Ullrich and Volk, 2009). For instance, conservation tillage or no-till, enhances soil organic carbon, soil quality, and soil aggregation leading to less soil erosion in agricultural landscapes (Roldán et al., 2007). CPs such as riparian vegetation, strip-cropping, and buffer strip can all help reduce diffuse pollutants, by reducing inputs to the crop, enhancing sequestration of nutrients in plant tissue, or reducing surface and subsurface losses due to hydrologic pathway alterations (Carpenter et al., 1998). However, it is not clear what impact a changing climate will have on the function of CPs. For instance, increased precipitation volume and intensity may overwhelm many CPs like riparian buffers, but higher temperatures, longer growing seasons, and more rainfall might cause that same buffer to mature more quickly, thus trapping more sediment and sequestering more nutrients. Thus, agricultural conservation practices need to be assessed for performance under a changing climate (Hatfield and Prueger, 2004).

In this study, we assess the effects of climate change on hydrology, water quality, and the effectiveness of agricultural conservation practices in Susquehanna River Basin. The Susquehanna River watershed is the largest source of nutrients and sediment to the Chesapeake Bay estuary and has been the focus of intensive agricultural CP implementation to reduce nutrient and sediment export from agricultural lands. The installation of CPs is largely driven by the U.S. Environmental Protection Agency (USEPA) Total Maximum Daily Load (TMDL) regulation to reduce nutrient and sediment to the Bay by approximately 25%. However, a major uncertainty with respect to CPs in the watershed is the complicating influence of climate change on their function and efficacy. The Susquehanna River basin is already experiencing the impact of a changing climate, with increasing temperatures reducing winter snowpack and increasing winter runoff, and more frequent high -intensity rainfall events mobilizing more sediment (Hayhoe et al., 2007). The predicted changes to climate in the region include continued increases in temperature, anywhere between 1 and 5 °C, dependent on emissions scenarios and season, more precipitation in the winter and spring, primarily as rainfall rather than snowfall, and less rainfall in the late summer and fall (Sheffield et al., 2013).

These changes in precipitation and temperature are likely to alter the timing and magnitude of streamflow and nutrient/sediment production and transport in the watershed. For instance, increased spring nutrient export from the watershed and delivery to estuary can set up conditions that cause particularly acute summer hypoxia (Boesch et al., 2001), and drier conditions in the summer and fall have been shown to increase the buildup of soil nutrients that can subsequently be flushed from the system when wet conditions return (Kaushal et al., 2008; Wetz and Yoskowitz, 2013). Temperature changes can alter nutrient cycling, plant growth, evapotranspiration, and soil water content, which all impact the availability and transport of nutrients from agricultural fields. Thus, CPs designed and installed to handle historic weather conditions may not function as well under a changing climate.

In this paper, we quantify the impact of climate change on agricultural CPs using the Soil and Water Assessment Tool-Variable Source Area (SWAT-VSA) model (Easton et al., 2008). SWAT-VSA is used because it is an existing platform to represent agricultural CPs, can simulate hydrologic and biogeochemical processes that are affected by climate change, and can easily incorporate many common agricultural CPs (Arabi et al., 2008). We analyze the results of each climate model, as well as the ensemble model mean, for their impact on hydrology and water quality with and without four CPs on agricultural lands in the Susquehanna River basin. In an effort to define optimal CP placement in the watershed, we leverage the ability of SWAT-VSA to represent the VSA hydrology that dominates the region and prioritize CP placement on the 30% of the agricultural lands that cause the greatest runoff, nutrient, and sediment losses (e.g., CSAs). The CSA targeting approach could provide a means for watershed managers or conservation personnel to prioritize CP placement across the landscape ultimately lowering costs and increasing water quality improvements.

2. Materials and methods

2.1. Study area description

The Susquehanna River basin contributes >50% of freshwater to the Chesapeake Bay, drains approximately 71,000 km^2, or 42% of the Bay watershed (Ko and Baker, 2004) and it's flow largely controls salinity in the Bay (Gibson and Najjar, 2000). The Susquehanna River Basin encompasses drainage areas in the states of New York, Pennsylvania, and Maryland, has six major sub-basins: Upper, Chemung, Middle, West Branch, Juniata, and Lower subbasins (Fig. 1) with elevations ranging from −10 to 960 m. The climate varies along a north -south gradient, with the northern portion of the basin receiving more precipitation (1240 mm/yr) than the lower basin (838 mm/yr) (DePhilip and Moberg, 2010). The land use of the basin consists of forest (70%), agriculture (22%), developed (7%), and water (1%). Soils are mainly silt loam or silty clay loam (Ray et al., 2016) with soil hydrologic group C ratings dominating, which have a moderately high runoff potential when thoroughly wetted (NRCS, 1998). The northern region of the basin is typified by steep to moderate hillslopes of glacial origins with shallow permeable soils, underlain by a restrictive layer that causes perched water tables to form. Soil depth ranges from <50 cm to >1 m and is underlain by a fragipan restricting layer (e.g. coarse-loamy, mixed, active, mesic, to frigid Typic Fragiudepts, Lytic or Typic Dystrudepts common to glacial tills). The southern region of the basin was never glaciated.

2.2. SWAT model description

The Soil and Water Assessment Tool (SWAT) model is a process-based, semi-distributed watershed model developed to simulate landscape processes and predict the impact of land management practices on water availability and water quality (Arnold et al., 1998). SWAT requires weather, soil, land cover, and land management data to simulate surface and subsurface hydrology and various chemical, nutrient, and sediment fluxes. In SWAT, the watershed is divided in to subbasins and then further in to hydrologic response units (HRUs), which are unique combinations of soil type and land use. SWAT-VSA reconceptualizes the standard SWAT to account for areas of the landscape subject to variable saturation dynamics (Easton et al., 2008). In SWTA-VSA the area of each HRU is defined by the coincidence of land use and wetness index class determined from a Topographic Index (TI) to differentiate areas of the landscape with respect to their moisture storage and saturation index (Easton et al., 2008). SWAT-VSA has been shown to provide better predictions of soil moisture and runoff generation than the standard SWAT model in watersheds with similar physical characteristics and climate to the study watershed (Easton et al., 2008). The version of SWAT-VSA used here also includes modifications to the P

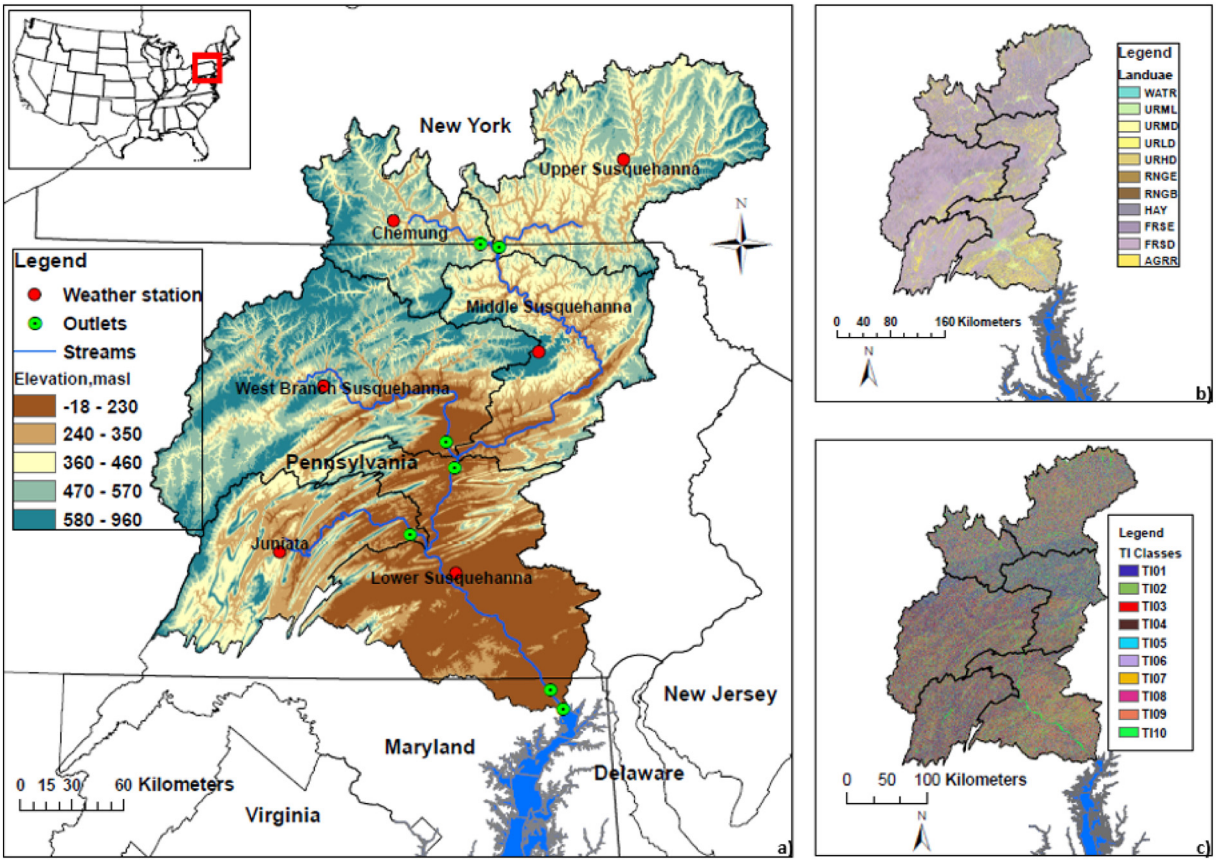

Fig. 1. Map of the Susquehanna River basin, major subbasins, and elevation in meter above sea level (a), land uses (b) where WATR (water); URML (Residential-Med/Low Density); URMD (Residential-Medium Density); URLD (Residential-Low Density); URHD (Residential-High Density); RNGE (Range-grasses); RNGB (Range-brush); HAY (Hay); FRSE (Forest-evergreen); FRSD (Forest-deciduous); and AGRR (Agriculture), and TI classes (c), are the topographic index wetness classes.

routines of Collick et al. (2016), which improves the simulations of surface applied P, particularly from manures. The watershed has six subbasins and 2903 hydrologic response units (HRUs).

2.3. Model inputs

The Susquehanna River SWAT-VSA model was developed with a 10 m digital elevation model (DEM) obtained from the United States Geologic Survey (USGS) National Elevation Dataset (NED) (Guenther and Maune, 2007) using ArcSWAT 2012 and TopoSWAT (Fuka and Easton, 2016). TopoSWAT automates the SWAT-VSA initialization process by assimilating soil data, creating the TI map, overlaying the soil and TI maps, and developing the required database for model initialization. Soils data included in TopoSWAT is based on Food and Agriculture Organization (FAO) soils database (FAO, 2007). TopoSWAT downscales the FAO soils data using the TI class as a proxy to distribute sand, silt and clay content, available soil water, hydraulic conductivity, bulk density, and soil depth, and has been shown to provide more accurate estimates of these parameters than finer resolution soils data such as SSURGO (Fuka and Easton, 2016). The land use of watershed was obtained from National Land Cover Database 2011, the most recent national land cover product created by the Multi-Resolution Land Characteristics (MRLC) Consortium (Homer et al., 2015). The model was forced with daily historic weather data from the Climate Forecast System Reanalysis (CFSR) (Fuka et al., 2014) gridded data, including precipitation, temperature (min and max), relative humidity, wind speed, and solar radiation from 1979 to 2014. Weather data for each subbasin were downloaded to the centroid of the six subbasins from http://cfsr.bse.vt.edu/swat-cfsr-v02.pl using the method developed by Fuka et al. (2014), an inverse distance weighting squared interpolation technique. This method has been tested in several different hydroclimatic regions and resulted in better model predictions of flow than using the nearest weather stations (Fuka et al., 2014). Rainfall intensity and duration is calculated by SWAT following Neitsch et al. (2011).

2.4. Model calibration and evaluation

Model calibration followed a cascading procedure, first calibrating all headwater basins (Upper Susquehanna, Chemung, West Branch, and Juanita subbasins) to observed USGS gage data. Next, the second order basin, the Middle Susquehanna was calibrated, leaving all parameters values for the headwater basins unchanged. Finally, the Lower Susquehanna subbasin was calibrated, leaving all parameter values for the headwater and second order basins unchanged. The model was calibrated and evaluated using SWAT Calibration and Uncertainty Procedure (SWAT-CUP) (Arnold et al., 2012) using the SUFI2 (Sequential Uncertainty Fitting) optimization algorithm with the objective function set to percent bias (PBIAS) method. The percent bias was used to ensure the model captured the mass balance, since the main focus of this work was quantifying the relative impact of climate change on BMPs rather than absolute daily prediction accuracy. The SWAT-VSA model performance was evaluated based on four metrics, PBIAS, the Nash Sutcliffe Efficiency coefficient (NSE), the normalized mean error (NME), and the normalized mean absolute error (NMAE) against the historical measured data for daily and monthly flow, and for monthly sediment, NO_3-N, and, TP from 1985 to 1994 for calibration and 2002 to 2011 for model evaluation. The NME is an index of relative bias, providing an estimate of overprediction (NME > 0) or under prediction (NME < 0) of the model. The NMAE (which is scaled relative to the observed mean) indicates discrepancy between model predictions and measured values,

the smaller the NMAE the closer model simulations are to observed values (Pourmokhtarian et al., 2012).

The daily observed flow data in the six subbasins were obtained from the USGS water data website available from (https://waterdata.usgs.gov/nwis/sw), and monthly sediment, TN, and TP fluxes data for the six subbasins were obtained from Hirsch et al. (2010) from (https://cbrim.er.usgs.gov/methods.html) using the Watershed Regression on Time Discharge Season (WRTDS) method. WRTDS is the USGS approved method to develop time series data from measurements (Chanat et al., 2016). The number of data points in the calibration and evaluation periods for daily flow was approximately 3650 each (from 1985 to 1994 for calibration and 2002 to 2011 for evaluation). For nutrients and sediment, WRTDS uses all available USGS data from the site, which varies by a constituent, but is usually 2–15 samples per month. During the calibration and evaluation periods, there were 1362 total water quality measurements made.

2.5. Incorporation of climate data

The most recent climate change models from the World Climate Research Programme's (WCRP's) Coupled Model Intercomparison Project Phase 5 (CMIP5) were obtained from the Earth System Grid Federation (ESGF): https://esgf-data.dkrz.de/projects/esgf-dkrz/ and include four scenarios: RCP2.6 (peak in radiative forcing at 2.6 W/m2 before 2100 and decline thereafter); RCP4.5 (stabilization without overshoot to 4.5 W/m2 at 2100); RCP6 (stabilization without overshoot to 6 W/m2 after 2100); RCP8.5 (increasing radiative forcing to 8.5 W/m2 by 2100). We elected to use two RCPs, RCP2.6 and RCP8.5, to represent the extremes of climate change potential on BMP performance. However subsequent testing revealed no significant differences between models forced with RCP2.6 and RCP8.5, based on an analysis of variance and a *t*-test at $\alpha < 0.1$. Thus, for all subsequent model runs and analyses, we used the mean of the RCP2.6 and RCP8.5 scenarios.

Six global climate models (GCMs) were selected based on work of Maloney et al. (2014) and Sheffield et al. (2013) that analyzed and ranked GCMs based on performance metrics to quantify the biases relative to observed seasonal precipitation, seasonal surface air temperature, and hydroclimate extremes (e.g., dry and wet days) in the Northeast and Mid-Atlantic US. The GCMs incorporated include the BCC-CSM1.1 (Beijing Climate Center, China Meteorological Administration), the CCSM4 (National Center for Atmospheric Research), the CSIRO-Mk3.6.0 (Commonwealth Scientific and Industrial Research Organization in collaboration with the Queensland Climate Change Centre of Excellence), the IPSL-CM5A-LR (Institut Pierre-Simon Laplace), the MIROC5 (Atmosphere and Ocean Research Institute The University of Tokyo, National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology), and the MPI-ESM-LR (Max Planck Institute for Meteorology).

Each of the six CMIP5 GCMs was downscaled and bias-corrected using a cumulative distribution function matching method, and the historical data from the GCMs were checked for bias/error correction against observed historical data (Li et al., 2010; Wang and Chen, 2014). This downscaling and bias correction was performed using the QMAP R package (Gudmundsson et al., 2012) and requires three separate data sets to complete the procedure: historical data as a downscaling reference, historical data from the climate model source, and future, or predicted data from the climate model source. The matching functions defined by each quantile of historical reference and historical modeled data are applied to the future modeled data. The accuracy of the historical, bias-corrected GCMs data from each of the models was verified by employing the Equiratio Cumulative Distribution Function (ECDF) matching method (Li et al., 2010) against the historical climate dataset. The detailed description of downscaling and bias-correction can be found from work in Wagena et al. (2016).

One potential shortcoming of quantile mapping is that it assumes that biases relative to historic observations are constant for the future periods (Camici et al., 2013; Thrasher et al., 2012). However, compared to other bias correction techniques, quantile mapping is efficient in removing bias (Camici et al., 2013), performs well for downscaling precipitation extremes (Chen et al., 2013) and has the benefit of accounting for GCM biases across all statistical moments (e.g., mean, variance, and skewness) (Camici et al., 2013), and thus is particularly sensitive to data in the tails.

The calibrated SWAT-VSA model then was forced by output of the six GCMs, including precipitation and minimum and maximum temperature for historical model runs (1990–2014) and two future periods (2041–2065 and 2075–2099) to analyze the impact of climate change on four selected agricultural CPs. We analyze the results of each climate model, as well as the ensemble model mean for their impact on hydrology, and water quality with and without the four CPs on agricultural lands in the Susquehanna River basin. In an effort to define optimal CP placement in the watershed, we leverage the ability of SWAT-VSA to represent the VSA hydrology that dominates the region and prioritize CP placement on the 30% of the agricultural lands that cause the greatest runoff, nutrient, and sediment losses.

2.6. Incorporation of agricultural conservation practices

The impact of climate change on agricultural CPs in the Susquehanna River Basin was evaluated by simulating four CPs in the model, which was then forced by the downscaled CMIP5 GCM data. We evaluated each of the CPs individually as well as the combined effect of all CPs installed together. We evaluated these CPs by simulating their extent on all of the agricultural HRUs in the watershed, representing a best-case scenario, and on the three highest agricultural TI classes, representing the 30% of the agricultural land most susceptible to runoff, and nutrient/sediment export. Evaluating the CPs performance on the most critical source areas in the watershed highlights the impact that targeting can have. The model was also run with no CPs for each future time period to serve as a baseline against which to compare CP implementation. Based on work of Arabi et al. (2008) CPs and the parameters controlling CP inclusion in the model were identified, and four agricultural conservation practices that are common in the region were simulated; buffer strips, strip cropping, no-till, and tile drainage.

2.7. Buffer strips

Field buffer strips consist of areas along stream channels or the edge of fields that are permeant, unharvested vegetation intended to reduce sediment and nutrient delivery from farm fields to surface water bodies. Buffer strips are modeled in SWAT by changing FILTERW parameter (width of buffer strip) and the parameter FILTERW is used to calculate trapping efficiency. Based on work of Bracmort et al. (2006), a 5 m buffer width was simulated.

2.8. Strip cropping

Strip cropping consists of narrow rows of alternating crop types and is commonly implemented in upland areas to reduce the surface runoff volume, the peak runoff rate, and rill and sheet erosion (Arabi et al., 2008). Based on work of Arabi et al. (2008), strip crops were represented in SWAT by lowering the curve number (CN) by three units to reduce surface runoff and peak flow rate, the USLE support practice factor (USLE_P) changed to 0.02 to reduce sediment export, and the Manning's roughness coefficient for overland flow (OV_N), which was increased to 25 to reduce peak flow and slow surface runoff.

2.9. Tile drainage

Tile drainage is implemented to drain excess water from the soil root zone to support crop growth. Tile drainage also reduces surface runoff from poorly drained soils. Tile drainage is represented in SWAT by

setting the depth to subsurface tile drain (DDRAIN) to 1 m, the drain tile lag time (GDRAIN) to 48 h, the drain spacing to 15 m, and effective radius of the tile drains to 50 mm.

2.10. No-till

No-till is the agricultural practice of growing crops without disturbing the soil through tillage, reducing erosion and sediment-bound contaminants. No-till was represented in the model by setting the tillage management operation to ZEROTILL in the management file, which means that there is no residue incorporation into the soil profile and changing the Manning's roughness coefficient for overland flow (OV_N), which was increased to 25 to reduce peak flow and slow surface runoff.

3. Results

3.1. Model performance evaluation

Table 1 shows the model performance for daily and monthly flow, and monthly sediment, NO_3-N, and TP export. According to Daniel et al. (2015) SWAT-VSA predicted all constituents reasonably well. The PBIAS values during calibration and evaluation period of both daily and monthly flow show a slight underprediction by the model, but the PBIAS and NSE values are all in the acceptable range based on the recommendations of Daniel et al. (2007) and Daniel et al. (2015) with the exception that the NSE values for NO_3-N and TP are slightly lower. The model slightly over predicted NO_3-N and TP during calibration (NME = 0.04, 0.20) period, respectively while it underpredicted NO_3- (NME = −0.37) and over predicted TP (NME = 0.21) during the evaluation period. The NME of the calibration and evaluation periods for sediment indicates under predictions (NME = −0.52, −0.16), respectively. The PBIAS values of sediment (PBIAS = 24.8, 16.4) shows the model underpredicts sediment, NO_3-(PBIAS = −4, 36.9) indicates overprediction of NO_3-,and TP (PBIAS = −19.9, −20.6) indicates the model overpredicts TP during calibration and evaluation periods respectively, and the PBIAS values are in range with recommended values by Daniel et al. (2015). The model performance was also evaluated for each subbasin for flow, and the model predicted both the daily and monthly flow very well during both calibration and evaluation (Table 1). Fig. 2 also shows scatter plot during the calibration and evaluation periods. The model predicted flow and sediment very well during the calibration and evaluation period, but missed some peak values of NO_3-N and TP during both periods.

3.2. Summary of climatic projections

Precipitation is predicted to increase in the watershed by 3.8% by mid-century and 6.5% by the end of the century (Table 2). The December–September period generally showed increases in mean monthly precipitation, while fall (October–November) generally showed decreases or no significant change in mean monthly precipitation (Table 2). On monthly basis, and for both scenario periods the largest increase is predicted to occur in January (14.2%, 2041–2065 and 10.4% 2075–2099). The largest decrease in mean monthly precipitation was predicted in October for both periods (5.1% in 2041–2065, and 3.0% in 2075–2099). Variability also increases across all months.

3.3. Temperature

Both RCP scenarios resulted in increases in mean annual temperature (maximum and minimum) during both scenario periods (Table 3). The predicted maximum annual temperature increases by 1.9 °C and by 2.8 °C while minimum annual temperature increases by 1.7 °C and by 2.7 °C during the 2041–2065 and 2075–2099 periods, respectively. The largest increase in maximum and minimum temperature is predicted to occur in April (2.3 °C and 2 °C) for the 2041–2065 period, while during the 2075–2099 period both August and September (3.1 °C and 3 °C) show the largest increases (Table 3).

3.4. Climate change effects on hydrology and water quality

The annual historic and future hydrologic budgets for the Susquehanna River basin are shown in Fig. 3. Annual runoff increases from 108 mm during the historic period to 111 mm and 114 mm during the 2041–2065 and 2075–2099 periods, respectively, while ground water contributions declined from 83 mm to 58 mm and 48 mm during the 2041–2065 and 2075–2099 periods, respectively. The largest changes to the hydrologic budget were for shallow interflow (LatFlow) and evapotranspiration (ET), which both increased substantially (Fig. 3).

Most climate models predicted an increase in mean annual flow during both scenario periods (Fig. 4a). The ensemble model mean predicts annual discharge to increase 4.5% and 8.9% for 2041–2065 and 2075–2099 scenario periods, respectively (Fig. 4a), although there was variability among models (−17.2 to +33.1%). The increase in mean annual flow is primarily due to a corresponding increase in lateral flow (Fig. 3), and runoff (Fig. 4b), there was a slight decrease in the contribution of groundwater flow to overall discharge (Fig. 3). Mean annual runoff increases by 3.3% in the 2041–2076 period and by 7.7% in the 2075–2099 period. Individual model predicted runoff ranges from −11.9 to +24.1% (Fig. 4b). Annual evapotranspiration increases by 4.8% and 8.0% during the2041–2065 and 2075–2099 periods, respectively (Fig. 3), due to an increase in temperature during both scenario periods (Table 3).

Mean annual sediment is predicted to increase by 25.8% and 30.9% during 2041–2065 and 2075–2099 periods, respectively (Fig. 4c), which is attributed to large increases in runoff for most models

Table 1
Percent bias (PBIAS), normalized mean error (NME), normalized mean absolute error (NMAE), and Nash Sutcliffe Efficiency coefficient (NSE) values for model calibration and evaluation periods.

	Daily								Monthly							
	Calibration				Evaluation				Calibration				Evaluation			
	PBIAS	NME	NMAE	NSE	PBIAS	NME	NMAE	NSE	PBIAS	NME	NMAE	NSE	PBIAS	NME	NMAE	NSE
Upper Susquehanna flow	−33.0	0.33	0.60	0.25	−11.4	0.11	0.45	0.49	−26.7	0.27	0.50	0.20	−5.1	0.05	0.35	0.52
Chemung flow	−8.6	0.09	0.60	0.53	−13.0	0.13	0.58	0.48	−10.4	0.10	0.52	0.48	−19.7	0.20	0.44	0.37
Middle Susquehanna flow	7.4	−0.08	0.43	0.55	−1.7	0.02	0.40	0.60	5.5	−0.05	0.37	0.53	−7.7	0.08	0.37	0.49
West Branch Susquehanna Flow	−8.4	0.08	0.42	0.57	−8.0	0.08	0.34	0.68	−7.0	0.07	0.36	0.44	−9.6	0.10	0.27	0.66
Juniata flow	−9.5	0.10	0.54	0.26	−8.0	0.08	0.44	0.59	−16.5	0.17	0.57	0.26	−10.8	0.11	0.33	0.69
Lower Susquehanna flow[a]	−5.2	0.05	0.40	0.63	−3.3	0.03	0.34	0.66	−5.1	0.05	0.30	0.62	−6.0	0.06	0.25	0.69
Lower Susquehanna sediment[a]	NA	NA	NA	NA	NA	NA	NA	NA	24.8	−0.25	0.74	0.42	16.4	−0.16	0.70	0.41
Lower Susquehanna nitrate[a]	NA	NA	NA	NA	NA	NA	NA	NA	−4.0	0.04	0.55	0.10	36.9	−0.37	0.46	0.29
Lower Susquehanna total phosphorus[a]	NA	NA	NA	NA	NA	NA	NA	NA	−19.9	0.20	0.50	0.14	−20.6	0.21	0.84	0.17

[a] Lower Susquehanna contains the watershed outlet.

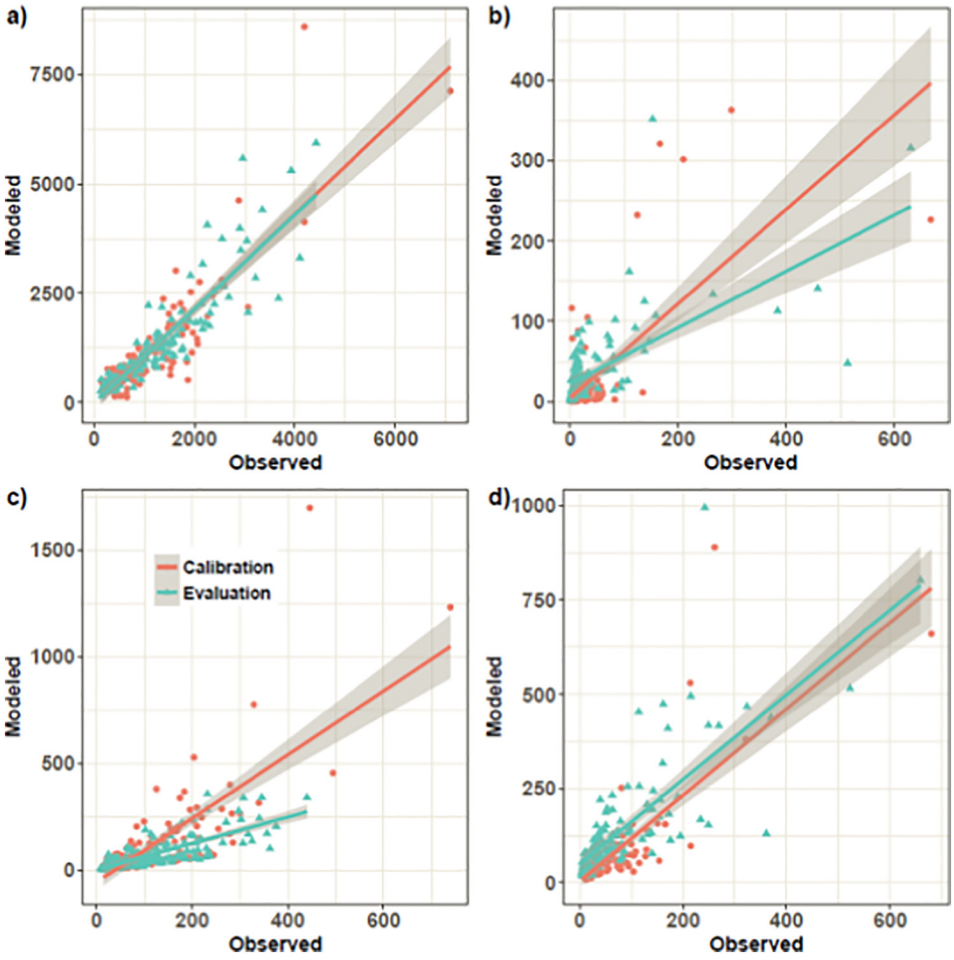

Fig. 2. Scatter plot of flow m^3/s (a), sediment $* 10^2$ t/month (b), NO_3-N $* 10^3$ kg/month (c), TP $* 10^2$ kg/month (d) during the calibration and evaluation periods.

(Fig. 4b) and rainfall intensity across all climate models. For instance, the MPI-ESM-LR climate model, which predicted runoff increases ranging from 59.1% to 70.3% predicted increases in rainfall intensity of 6.5% and 10.1% during mid-century and end-of-century, respectively. Even models that predicted reduced runoff; the IPSLCMA.LR and BCC·CSM1.1 models, result in increased sediment export. This is due to two factors, one is the timing of precipitation, both models had a greater fraction of their precipitation in the winter, when there is less ground cover, and second, both models had greater precipitation intensity compared to the other models.

Relative to historical climate record, NO_3-N export is predicted to decrease while TN export increases during both scenario periods. The ensemble model mean suggest a decrease in NO_3-N export of 9.2% for 2041–2065 and 14.7% for 2075–2099 (Fig. 4d). During the 2041–2065 period, the greatest decrease in NO_3-N export was predicted by BCC-CSM1.1 (35.1%) while the MIROC5 and IPSLCMA.LR models predicted slight increases (4.5% to 11.9%) while by end-of-century all models result in decreases in NO_3-N export (Fig. 4d). The model mean TN export increases by 8.9% for the 2041–2065 period and 11.6% for the 2075–2099 period. There was a strong consensus among all models that TN export will increase in both periods (Fig. 4e).

Table 2
Percent precipitation change from the historic period (1990 to 2014) for the ensemble model mean for mid-century (2041 to 2065) and end-of-century (2075 to 2099).

Month	Mid century	End century
Jan	14.2	10.7
Feb	5.7	10.4
Mar	4.1	8.5
Apr	1.3	1.7
May	2.4	10.1
Jun	3.2	3.8
Jul	6.8	9.6
Aug	2.1	6.2
Sep	5.0	10.4
Oct	−5.1	−3.0
Nov	0.8	2.0
Dec	4.7	7.7
Annual	3.8	6.5

Table 3
Change in monthly maximum and minimum temperature (°C) compared to the historical period (1990 to 2014) for the ensemble model mean for mid-century (2041 to 2065) and end-of-century (2075 to 2099).

Month	Mid century		End of century	
	Tmax	Tmin	Tmax	Tmin
Jan	1.7	1.8	2.4	2.7
Feb	1.8	1.9	2.6	2.7
Mar	2.0	1.7	2.4	2.1
Apr	2.3	2.0	3.0	2.8
May	1.8	1.6	2.9	2.7
Jun	1.8	1.7	2.8	2.6
Jul	1.9	1.8	3.0	2.9
Aug	1.8	1.7	3.1	3.0
Sep	1.9	1.8	3.1	3.0
Oct	1.7	1.3	2.7	2.4
Nov	1.7	1.5	2.6	2.5
Dec	1.8	1.8	2.6	2.7
Average	1.9	1.7	2.8	2.7

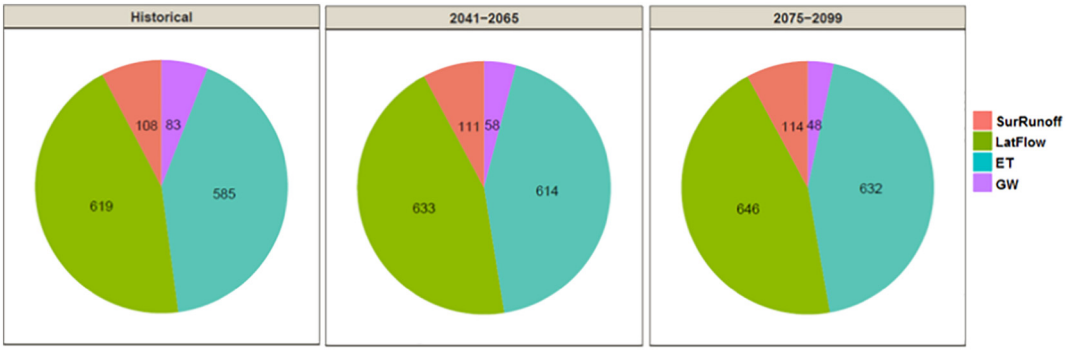

Fig. 3. Hydrologic budget for historical and future periods (all units are in mm).

Most climate models predicted a decrease in both TP and DP during both scenario periods (Fig. 4f and g). The model mean annual DP export deceaseses by 16.4% for the 2041–2065 period and 11.8% for the 2075–2099 period, with only the MIROC5 model predicting a slight increase of 4.9% during the 2041–2065 period. Mean annual TP decreases by 4.5% for the 2041–2065 period and 2.1% for the 2041–2065 period (Fig. 4g). There was more variability among individual models for TP than DP, with an increase in TP export predicted by three models, and a decrease by three models. The decrease in DP is driven by decreases in mineralization of fresh organic P in the soil, by 11.8% and 18.2% during 2041–2065 and 2075–2099 periods, respectively. This results in decreased DP (and by extension, TP) export of 10.3% and 8.6% during 2041–2065 and 2075–2099, respectively (Fig. 4f, d). This is despite an increase in surface runoff and sediment export (Fig. 4b, c).

3.5. Impact of agricultural CPs on hydrology under climate change

Agricultural CPs are simulated for both future time periods assuming: 1) CPs are installed across all agricultural HRUs evenly, and 2) CPs are installed on the 30% of the agricultural HRUs generating the most runoff (e.g., CSAs). As is shown in Fig. 5a most CPs have little effect on watershed level discharge compared to the No Practice scenario. Tile drainage reduced discharge approximately 2.7%, which is also reflected in the combined CP scenario (Fig. 5a). Fig. 5a shows that while there is

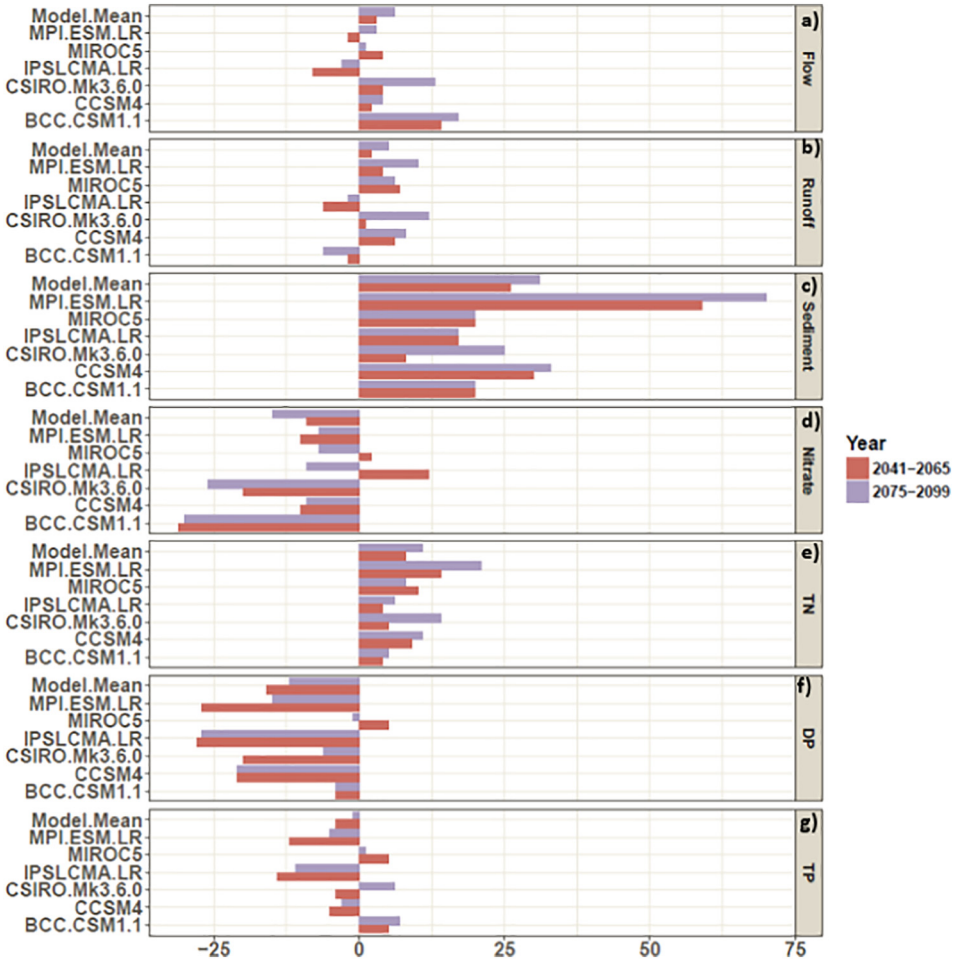

Fig. 4. Percent change from the historical baseline for flow (a), runoff (b), sediment (c), nitrate (d), total nitrogen (e), dissolved phosphorus (f), and total phosphorus (g) for the six induvial climate models, and two future climate periods.

not any substantial change in flow for mid-century, there is a significant increase in flow for the late century period, and again, only tile drainage has any noticeable effect on discharge. However, runoff generation in the watershed was affected by the CPs (Fig. 5b). Tile drainage reduced runoff generation approximately 4% in both periods, while strip cropping and no-till resulted in a reduction of approximately 2%. The combined effect of all the CPs reduced runoff generation by approximately 4%. The buffer strip CP had no appreciable impact on runoff generation (Fig. 5b).

3.6. Impacts of agricultural conservation practices on water quality under climate change

When agricultural CPs are installed across all agricultural HRUs in the watershed the sediment load was greatly reduced compared to the No Practice scenario, and for some CPs the reduction in sediment export approached historical export, particularly during the 2041–2065 period (Fig. 5c). The greatest sediment load reductions were achieved when buffer strips and tile drainage were installed followed by no-till and strip-cropping. Annual sediment reductions (compared to the No Practice scenario) range from 19.5% (2041–2065) to 20.2% (2075–2099) for tile drainage, 19.5% (2041–2065) to 19.9% (2075–2099) for buffer strip, and 20.4% (2041–2065) to 20.8% (2075–2099) for the combined CPs (Fig. 5c). Fig. 5c also shows that, in general, CPs tended to reduce the intra-annual variability of sediment export compared to both the historic period and the No Practice scenario, in particular, no-till and tile drainage. There is slightly greater intra-annual variability in the 2075–2099 period than the 2041–2065 period.

Most CPs resulted in a decrease in NO_3-N export compared to the No Practice and the historical model (Fig. 5d). Buffer strips, no-till, and strip crop CPs reduced NO_3-N export by 11.5%, 2.1%, and 2.3%, respectively in the 2041–2065 period, and 9.3%, 3.8%, and 4.1%, respectively in the 2075–1099 period. Tile drainage substantially increased NO_3-N export by 15.2% for the 2041–2065 and 14.8% for the 2075–2099 periods compared to the No Practice scenario (Fig. 5d). This increase is primarily due to increased nitrification occurring after tile drainage is installed; tile drainage increases root zone aeration, increasing the conversion of ammonium to NO_3-N, which is considerably more mobile in the soil. Tile drainage also removes excess soil moisture, which when coupled with higher soil NO_3-N levels dramatically increases N export. Compared to the historical export the buffer strip decreases NO_3-N by 18.1% in 2041–2065 and 23.7% in 2075–2099, strip cropping by 11.5% for 2041–2065 and 17.5% for 2075–2099, and no-till 11.5% for 2041–2065 and 17.5% for 2075–2099 (Fig. 5d).

The CPs resulted in slightly different TN responses than more mobile NO_3-N (Fig. 5e), with all CPs, including tile drainage reducing TN export compared against the No Practice scenario. The buffer strip CP was most effective in reducing TN export, resulting in an 11.4% and 17.1% reduction during the 2041–2065 and 2075–2099 periods, respectively. Tile drainage reduced TN export by 6.1% and 10.2% during the 2041–2065 and 2075–2099 periods, respectively. No-till and strip crop produced lower reductions, ranging from 1.3–3.2% for no-till and 2.9–5.8% for strip crop. The CPs also lowered the intra-annual variability in TN export.

All CPs were effective in reducing both DP and TP export compared to both the historical and future periods without CPs. Tile drainage and buffer strips tended to be the most effective at reducing P export,

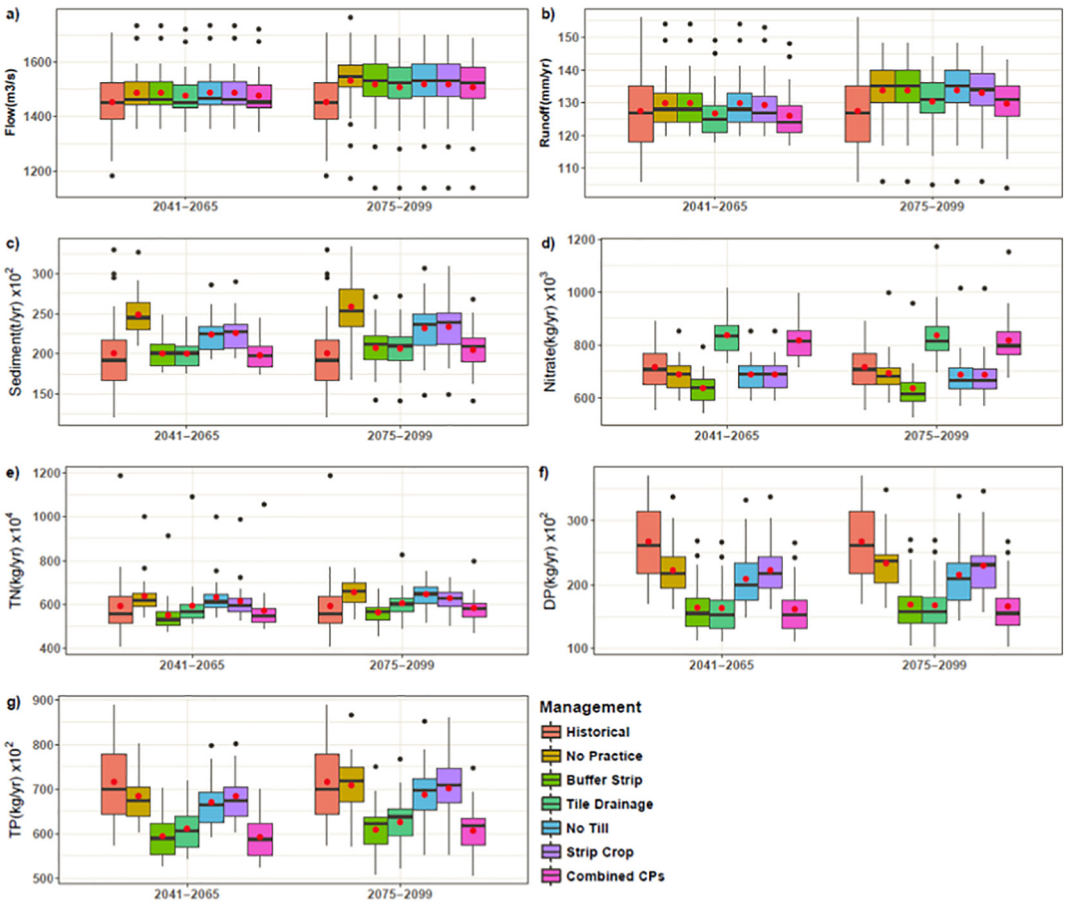

Fig. 5. Box plot (1st, median, mean (red dot) and 3rd quartiles) of historical (1990–2014) and future (2041–2065 and 2075–2099) average-by-year streamflow (a), runoff (b), sediment (c), nitrate (d), total nitrate(e), dissolved phosphorus (f), and, total phosphorus (g) for five agricultural conservation practices under the six climate models, at the watershed outlet.

with buffer strips slightly more effective at reducing TP, and tile drainage slightly more effective at reducing DP (Fig. 5f, g). When tile drainage was implemented annual DP export decreased by 39.0% and 37.4% while TP export decreased by 14.5% and 12.6% during 2041–2065 and 2075–2099, respectively compared to the No Practice scenario (Fig. 5f, g). This is due to capability of tile drains to reduce surface erosion and surface runoff (Fig. 5b, c) which are the main drivers for sediment-associated P export (note SWAT does not simulate P chemistry in tile drainage, Kleinman et al., 2015; Radcliffe et al., 2015, so the impact is entirely associated with the hydrological and sediment effects). Dissolved P export deceased for the buffer strip (29.4% and 36.9%), no-till (7.8% and 13.4%), and strip crop (4.3% and 11.1%) compared to the No Practice scenario during the 2041–2065 and 2075–2099 periods, respectively (Fig. 5f). Buffer strips reduced TP export by 16.4% and 14.2% during the 2041–2065 and 2075–2099 periods, respectively (Fig. 5g). Total P export decreased for no-till 3.4% and 5.1% compared to the No Practice scenario during the 2041–2065 and 2075–2099 periods, respectively (Fig. 5g). Strip crop was essentially ineffective in reducing TP export during both periods.

3.7. Implementation of agricultural conservation practices on agricultural critical source areas (CSAs)

Implementing agricultural conservation practices on the 30% of the agricultural land that generates the greatest runoff volumes (e.g., CSAs) has very little impact on watershed level discharge during the 2041–2065 period, but all CPs result in an approximately 2.0–2.5% decrease in flow during the 2075–2099 period (Fig. 6a), coupled with greater intra-annual variability. For surface runoff (Fig. 6b) only tile drainage resulted in a decrease of approximately 3% in both periods, the other CPs had no discernible impact on runoff generation.

In general, CSA targeting resulted in nearly the same reductions for most constituents as the more widespread implementation. For instance, implementing no-till on CSAs decreased sediment load by 1.2% and 1.5% for the 2041–2065 and 2075–2099 periods, respectively, compared to 1.3% and 1.7% for the 2041–2065 and 2075–2099 periods, respectively when implemented on all agricultural land (Figs. 5c and 6c). Tile drainage is the only practice that resulted in an increase in any constituent and that was for NO_3-N, however, the increase in NO_3-N export was similar for both the CSA targeting (12.5% to 14.3%) and the widespread implementation (16.2% to17.5%) scenarios (Figs. 5d and 6d).

Fig. 7 compares the relative reductions achieved by widespread CP implementation and CSA targeting. Across almost all CPs there was very little difference between the two methods. For total watershed flow and surface runoff only tile drainage resulted in slightly different results, with the widespread implementation reducing flow and surface runoff slightly more than the CSA targeting in both periods (Fig. 7a, b). For sediment, widespread CP implementation reduced sediment export more than for CSA targeting, particularly for the buffer strip, tile drainage, and strip cropping CPs (Fig. 7c). No-till did not result in appreciable differences between widespread implementation and CSA targeting. For NO_3-N, only the buffer strip CP provided greater relative reductions for widespread implementation, and tile drainage, implemented widely, resulted in substantially greater NO_3-N export than if it were only implemented in CSAs (Fig. 7d). Similar results occur for TN, widespread implementation of buffer strips reduced TN loss substantially more than CSA targeting (14.1% and 16.0% below the No Practice scenario in

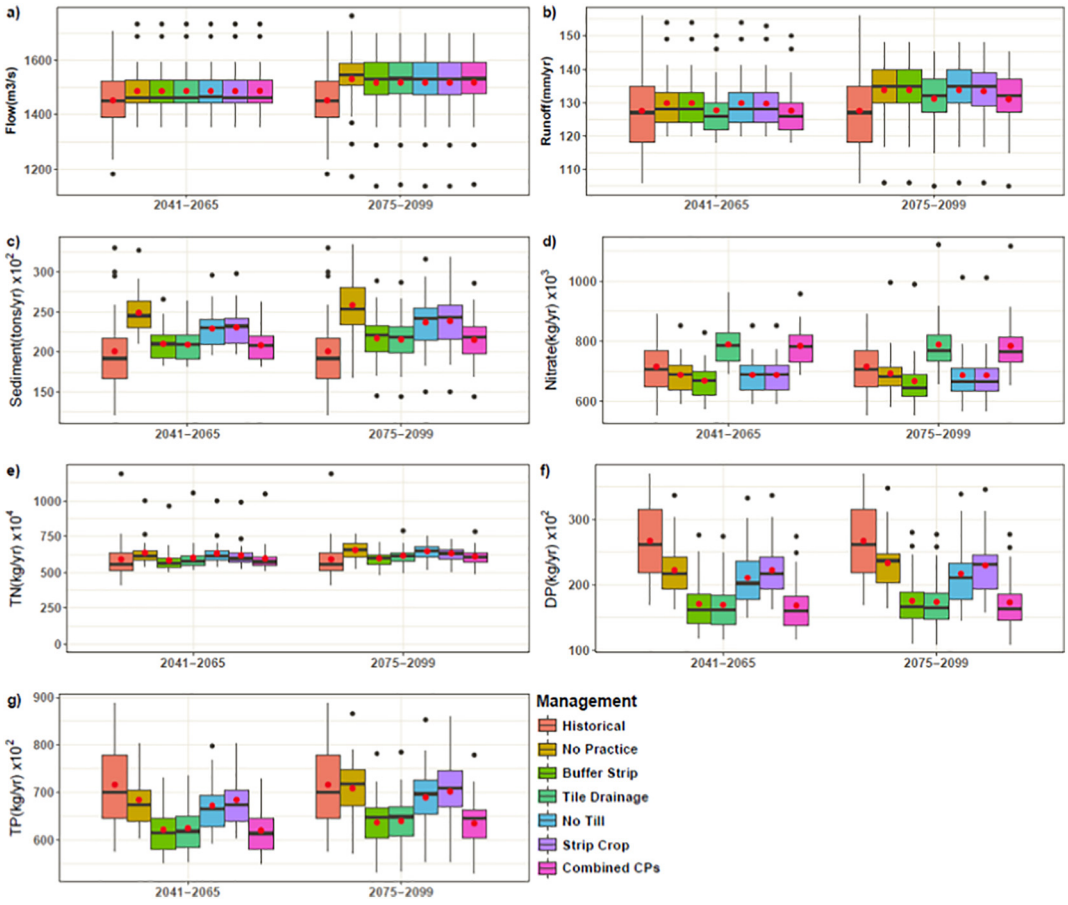

Fig. 6. Box plot (1st, median, mean (red dot), and 3rd quartiles) of historical (1990–2014) and future (2041–2065 and 2075–2099) average-by-year streamflow (a), runoff (b), sediment (c), nitrate (d), total nitrate (e), dissolved phosphorus (f), and total phosphorus (g) for five agricultural management practices implemented at critical source areas under the six climate models.

2041–2065 and 2075–2099, respectively for widespread implementations and 8.4% and 10.1% below the No Practice scenario in 2041–2065 and 2075–2099, respectively for CSA targeting, Fig. 7e). Tile drainage resulted in greater TN loss when implemented widely during both periods (Fig. 7e), however, the export was still less than the No Practice scenario. Results of CSA targeting for both DP and TP show that buffer strip and tile drainage reduced losses slightly more when implemented widely than for CSA targeting, with additional reductions of approximately 1–5% depending on practice and time period (Fig. 7f, g).

4. Discussion

Climate change is likely to affect the water quality of the Susquehanna River Basin. However, implementing PPs on agricultural lands can offset much of the impact. The river basin is predicted to receive more annual precipitation by the mid and end-of-century periods (Table 2) with a concomitant increase in temperature (Table 3) and ET (Fig. 3). The predicted increase in mean annual precipitation (3.8%) by the mid-century and (6.5%) the end-of-century are consistent with work of Najjar et al. (2009), who predicted increases in precipitation over the Chesapeake Bay watershed of 3% to 12% using NARCCAP data derived from the CMIP3 A2 (medium-high emission scenario) dataset and Howarth et al. (2006) who predicted an increase in precipitation of 4% and 15% during the 2030 and 2095 periods, respectively. These increases in precipitation and temperature affect processes such as nutrient cycling, snowfall, and soil moisture, which translate into altered water quality, and affect CP performance (Bosch et al., 2014).

Increases in flow, interflow, and surface runoff relative to the historic period result in substantial increases to sediment export, although the magnitude of the change differs among the climate models. Hayhoe et al. (2007) and Najjar et al. (2010) predicted similar increases in flow during spring driven by greater precipitation and deceaseses in summer driven by increased ET. The predicted increase in flow will force existing CPs to deal with more runoff and can impact their effectiveness and/or force managers to design new practices to accommodate increased runoff. Because of these predicted increases in runoff and sediment export, CPs become that much more important to achieve current water quality goals in the Chesapeake Bay and to maintain the current export into the future.

Most CPs had no effect on surface runoff, implemented either widely or targeted to CSAs except, for tile drainage (Figs. 5a, 6a). When tile drainage is installed on agricultural lands, there is a decrease in surface runoff compared to corresponding periods without tile drainage (Figs. 5a, and 6a). Tile drainage removes free soil water, increasing the soil moisture storage capacity and infiltration (Madramootoo et al., 2007), consequently reducing runoff and the associated soil erosion and P loss, (King et al., 2014), but increases NO_3-N loss (Figs. 5 and 6). The substantial increase in NO_3-N loss associated with tile drainage has been well documented (Randall and Goss, 2008), and occurs due to several factors. Tile drainage, by way of increased soil aeration, increases nitrification (Stark and Firestone, 1995), making more NO_3-N available (Dinnes et al., 2002), and since NO_3-N is soluble, it is easily exported from tile-drained fields. The strip cropping and buffer strip CPs did not affect surface runoff but were effective in reducing NO_3-N export, even below the historic value (Figs. 5a and 6a), due primarily increased nutrient uptake in plant biomass and their ability to reduce surface runoff generation. Although most model scenarios predicted a decrease in NO_3-N, all predicted an increase in TN (Fig. 4d, e). This decrease in NO_3-N is due to increased denitrification from warmer temperatures and higher soil moisture, while the increase in TN is driven primarily by a decrease in both mineralization and nitrification, particularly during the drier summer periods (Groffman et al., 2009) allowing

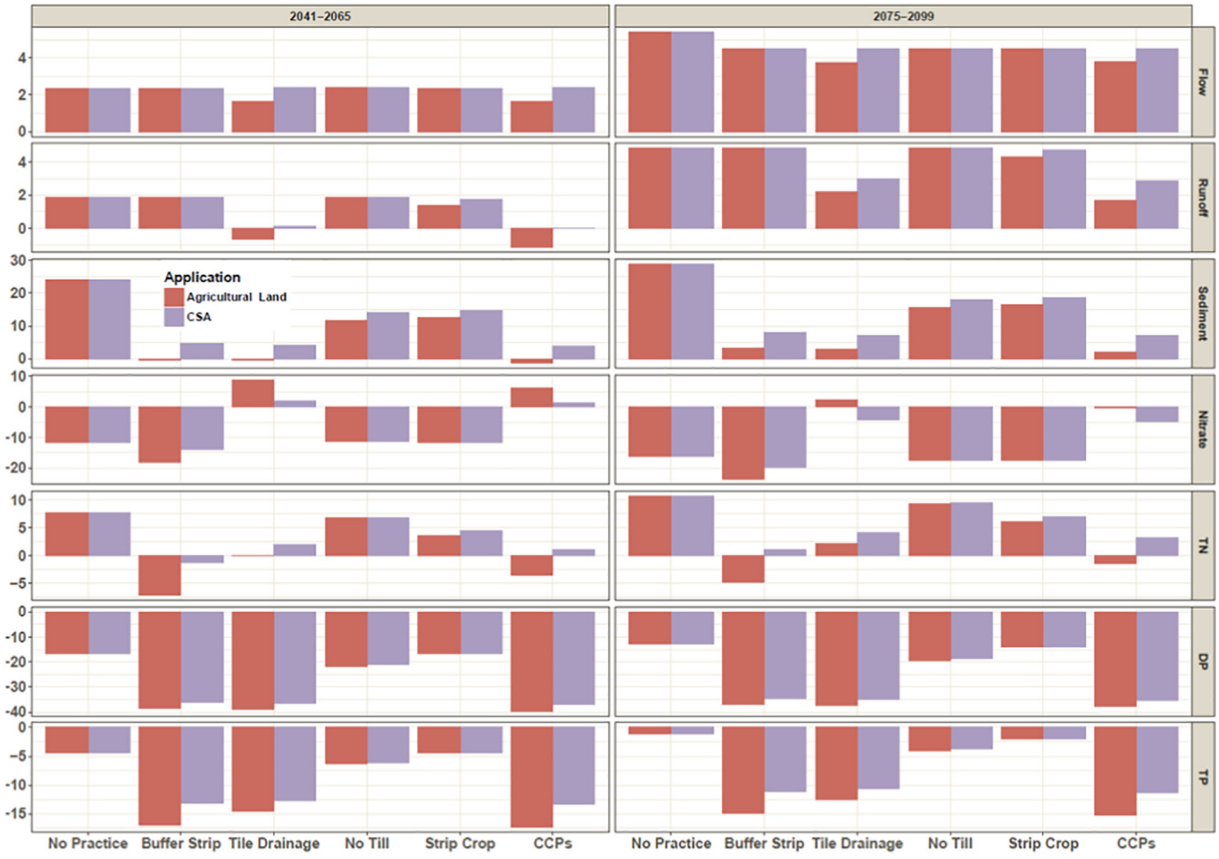

Fig. 7. Comparison of annual changes (%) for two future (2041–2065 and 2075–2099) time periods for flow (a), runoff (b), sediment (c), nitrate (d), total nitrogen (e), dissolved phosphorus (f), and total phosphorus (g) for four agricultural practices (note: CCPs in the figure stands for combination of all conservation practices) and no the CP scenario, implemented on all agricultural landuses and only on critical source areas (CSA) relative to the historical scenario (1990–2014) for the watershed outlet.

more soil TN build up. Most CPs reduce TN export, and the buffer strip was able to reduce export below the historic value (Figs. 5g and 6g). Tile drainage was more effective at reducing TN loss than a NO_3-N loss because TN is not as mobile in the soil.

The increase in sediment export is mainly driven by increases in runoff predicted by most climate models (Fig. 4b), or precipitation intensity causing erosion from upland areas (Langland and Cronin, 2003). The predicted increase in sediment export would have major impacts on Chesapeake Bay function, reducing clarity, and burying aquatic vegetation (Zhang et al., 2013) and on watershed infrastructure. Indeed, Cerco (2016) found that the Conowingo Dam reservoir on the lower Susquehanna (the largest reservoir in the basin) is currently in a state of dynamic equilibrium in which the sediment inflow and outflow are balanced, thus the projected increase in sediment is unlikely to be stored in the watershed, but rather will be exported to the Bay. Our results show implementing CPs reduces the effect of climate change on sediment export by 1.3% to 20.8%, particularly tile drainage, no-till, and buffer strips (Figs. 5c and 6c). The effect of tile drainage (and to some extent no-till) is entirely realized through reductions in surface runoff, while the buffer strip and no-till effect is a result of sediment trapping by the buffer vegetation. Others have also shown buffer strips to be effective at controlling sediment export from agricultural fields (Arabi et al., 2008; Blanco-Canqui et al., 2004; White and Arnold, 2009). Widespread implementation of no-till reduced sediment export by approximately 10.0% during both periods for widespread implementation, and by approximately 8.5% for both periods when implemented on CSAs (Figs. 5c and 6c).

Both DP and TP export decrease in the basin under climate change; for DP the reductions range from 15.7% to 12.4% during 2041–2065 and 2075–2099 periods, respectively and for TP the reductions range from 4.5% to 2.6% during 2041–2065 and 2075–2099 periods, respectively (Fig. 4f and g), which is consistent with Roberts et al. (2009) for the Chesapeake Bay, who predicted a 19% reduction in P. It is somewhat surprising that both DP and TP decreased in the future, although the TP decrease was relatively small, and there was considerable viability among models (Fig. 4g), given the large increases in runoff and sediment export. However, more P is taken up in plant and possibly microbial biomass under warmer and wetter conditions, which would utilize DP rapidly if it was not buffered by desorption and dissolution reactions (Fitter and Hay, 2012). This coupled with reduced P mineralization from fresh organic P of 11.8% and 18.2% during the 2041–2065 and 2075–2099 periods, respectively results in the predicted DP reductions. Increasing soil TN may also stimulate plant growth resulting in increased P uptake by the plant, this may also partially explain the decline in NO_3-N. When CPs are installed P export decreases compared to future periods with no CPs, although there is variability in the magnitude of the changes among practices (Figs. 5f and 6f). Tile drainage and buffer strip resulted in the greatest reduction in both DP and TP export compared across all time periods and scenarios, substantially below the historic P export. The no-till and strip crop CPs resulted in smaller P reductions than the tile drainage and buffer strip, but were still able to offset the impact of climate change during both future periods (Figs. 5e and 6e). Reductions achieved by installing CPs on CSAs were only slightly lower than widespread CP installation.

These results indicate that for sediment and TN, maintaining current CP extent will not be sufficient to meet water quality goals in the region under a changing climate. For pollutants such as sediment and TN significant remediation effort will be required to offset/reduce impact of changing climate on water quality in the basin. However, the effectiveness of CPs implementation depends on the type of practices used and the pollutant of concern. For instance, implementing tile drainage over buffer strips or strip crops might result in pollution swapping (e.g., increased NO_3-N loss, but decreased sediment and P loss). Thus, managers tasked with improving water quality will need to weight the relative performance of CPs for specific pollutants before deciding which to install. Furthermore, it should be noted that maintaining current levels of nutrient and sediment export is not sufficient to meet the TMDL currently in place, which calls for reductions of 25%, 24%, and 20% for nitrogen, phosphorus, and sediment by 2025.

5. Conclusions

Climate change is likely to have impact on water quality in the Chesapeake Bay watershed, however, implementing CPs can reduce this impact. Our results suggest that climate change will result in an increase in flow, surface runoff, sediment, and TN. However, installing CPs on agricultural land can sustainably reduce these losses. Irrespective of CP installation, increased crop growth and altered biogeochemical processes associated with a changing climate can also reduce losses, particularly for soluble nutrients such as DP and NO_3-N, and CPs can further reduce these losses. Maintaining current condition will not be sufficient to meet water quality goals of Susquehanna River and Chesapeake Bay under changing climate. Thus, managers need to focus on developing new agricultural conservation practice and/or use combination of agricultural conservation practices to fully offset the effect of changing climate on water quality.

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